# **Reconstructing Primordial non-Gaussianity**

Thomas Flöss (University of Groningen) - Sesto Workshop - 04/07/2024

### Based on...

- 2206.10458 TF, Matteo Biagetti & Daan Meerburg
- 2305.07018 TF & Daan Meerburg
- 24xx.xxxx Jelte Bottema, TF & Daan Meerburg

### "How to optimally extract primordial non-Gaussianity from large-scale structure?"

## What's wrong with the bispectrum?

- CMB is linear, LSS is highly non-linear
- Signal confusion (secondary non-Gaussianity)
- Mode coupling (non-Gaussian covariance)

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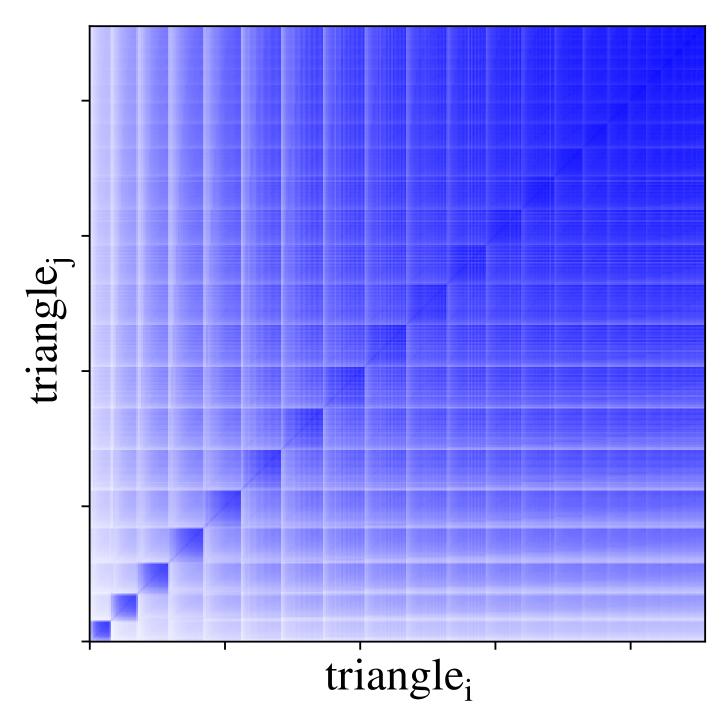


Figure: correlation matrix of non-linear matter bispectrum

# What's wrong with the bispectrum?

- CMB is linear, LSS is highly non-linear
- Signal confusion (secondary non-Gaussianity)
- Mode coupling (non-Gaussian covariance)

- Constraints saturate
- Information moved to higher-order correlation functions

Biagetti++ 2021, Coulton++ 2022, Goldstein++ 2022, TF++ 2022

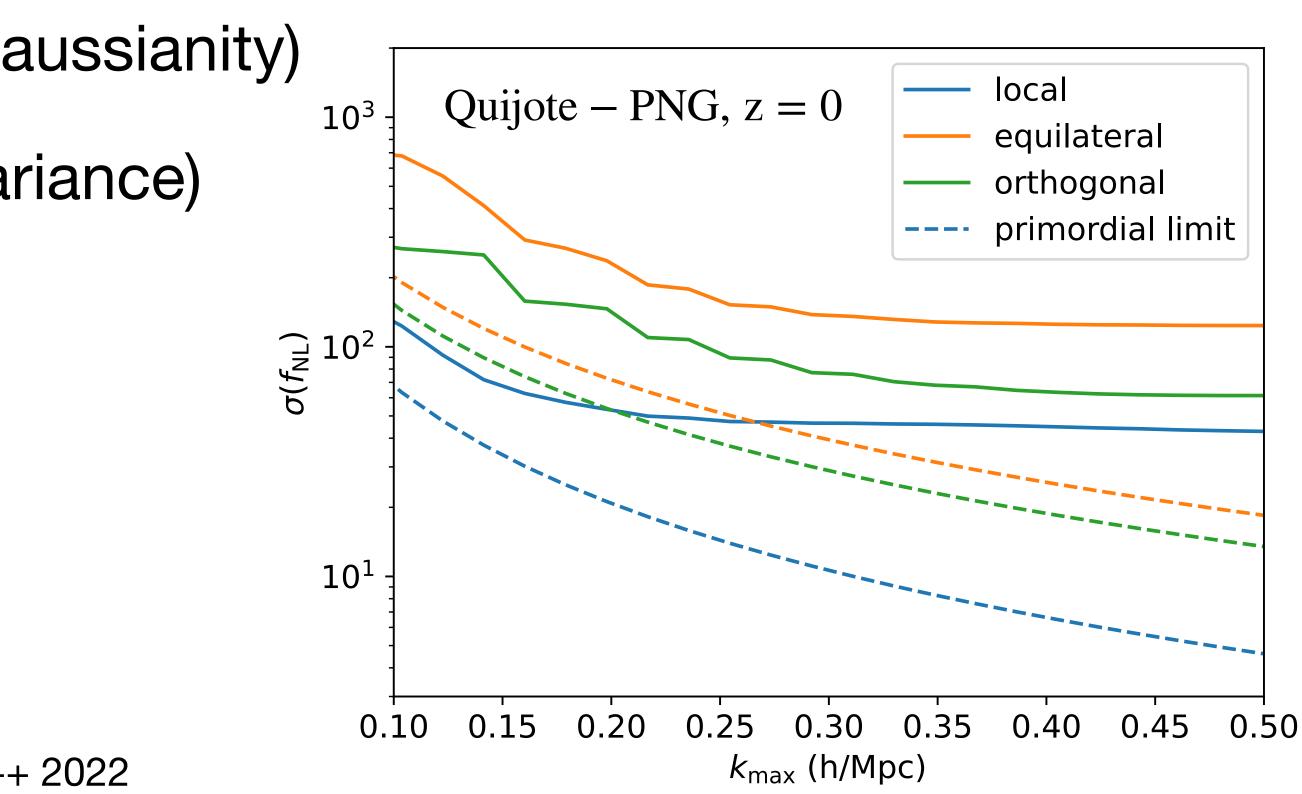


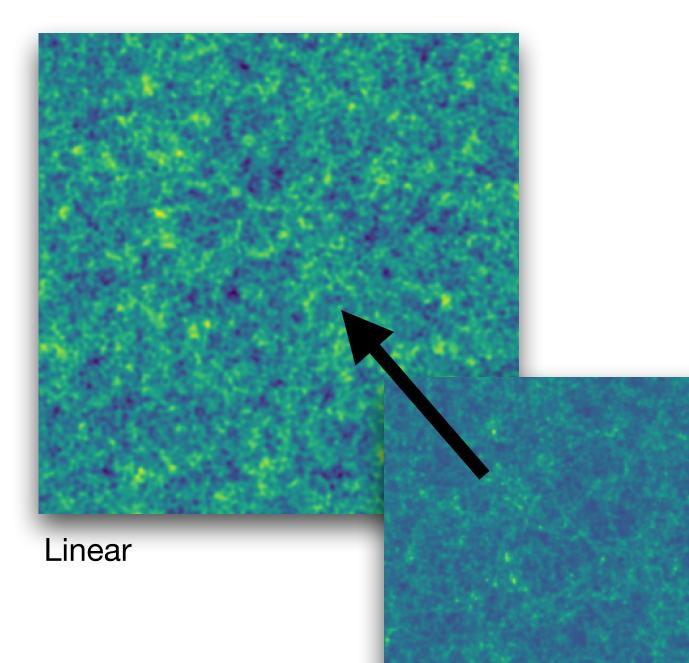
Figure: Fisher forecast on  $f_{\rm NL}$  from non-linear matter bispectrum

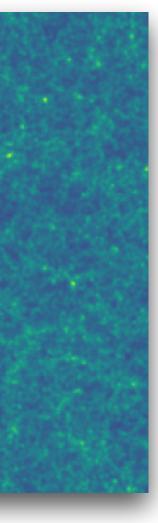
### What now?

- Scale dependent bias helps local pnG, but not equilateral
- Higher-order correlations: expensive, inefficient
- Field contains all the information: how to extract it?

## **Reconstructing the linear density field**

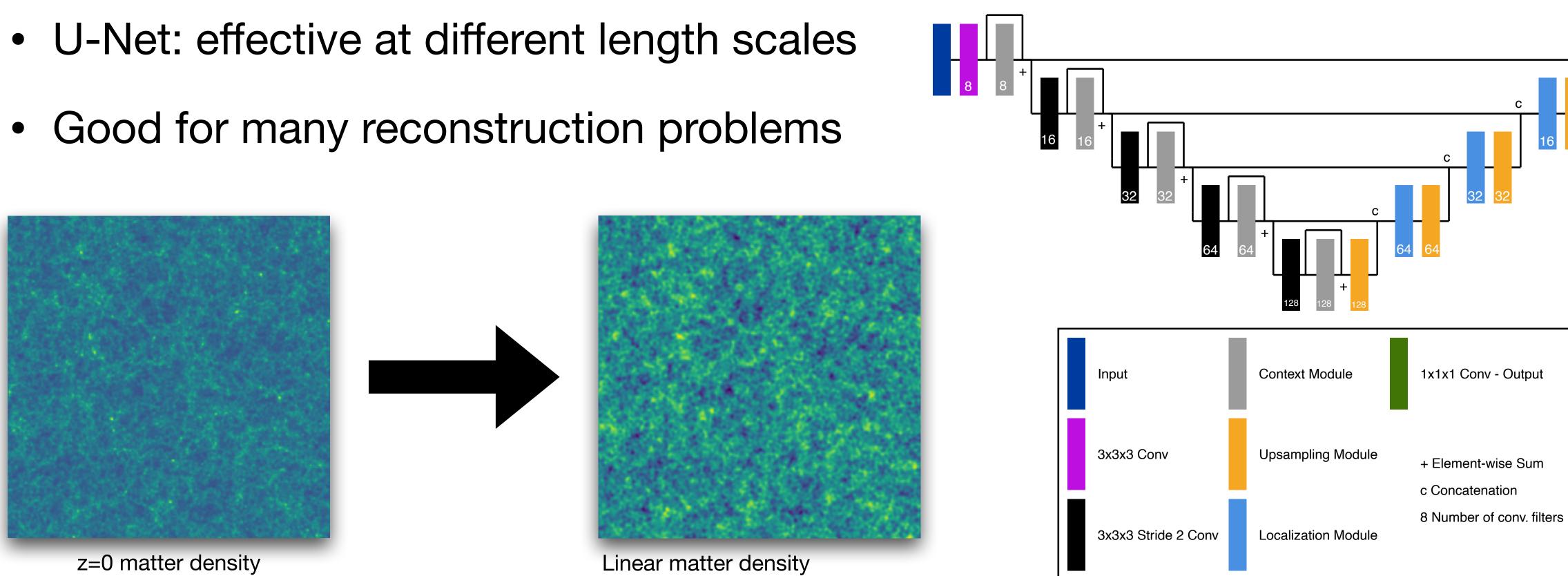
- Linear matter bispectrum contains all information on pnG  $\bullet$
- Reconstruction decouples modes
- Moves information back to the bispectrum
- Constrain cosmology from the reconstructed field



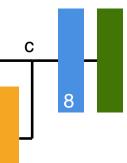


### **Neural reconstruction** 2305.07018 TF & Daan Meerburg

- Image type data: Convolutional Neural Network

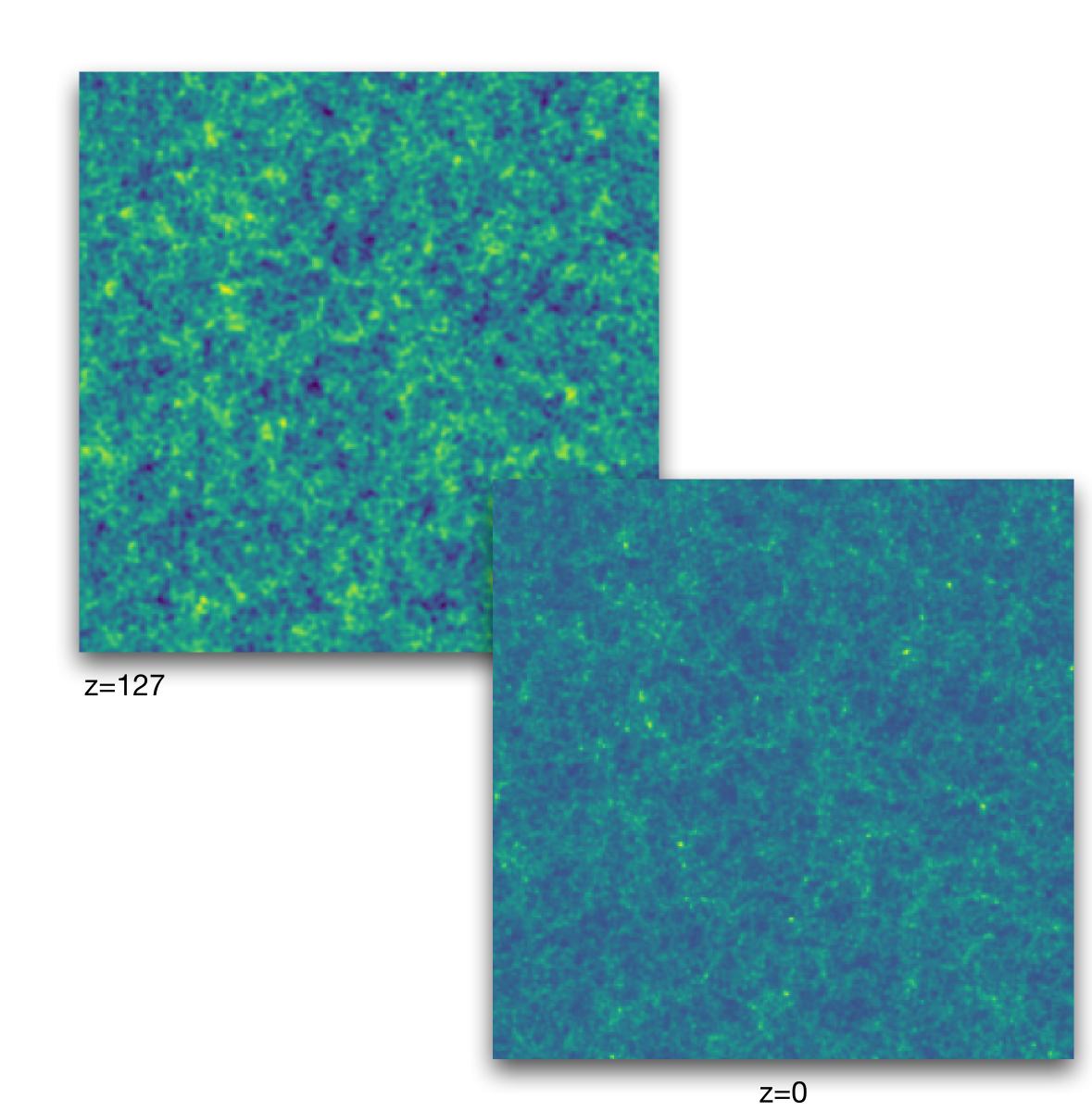






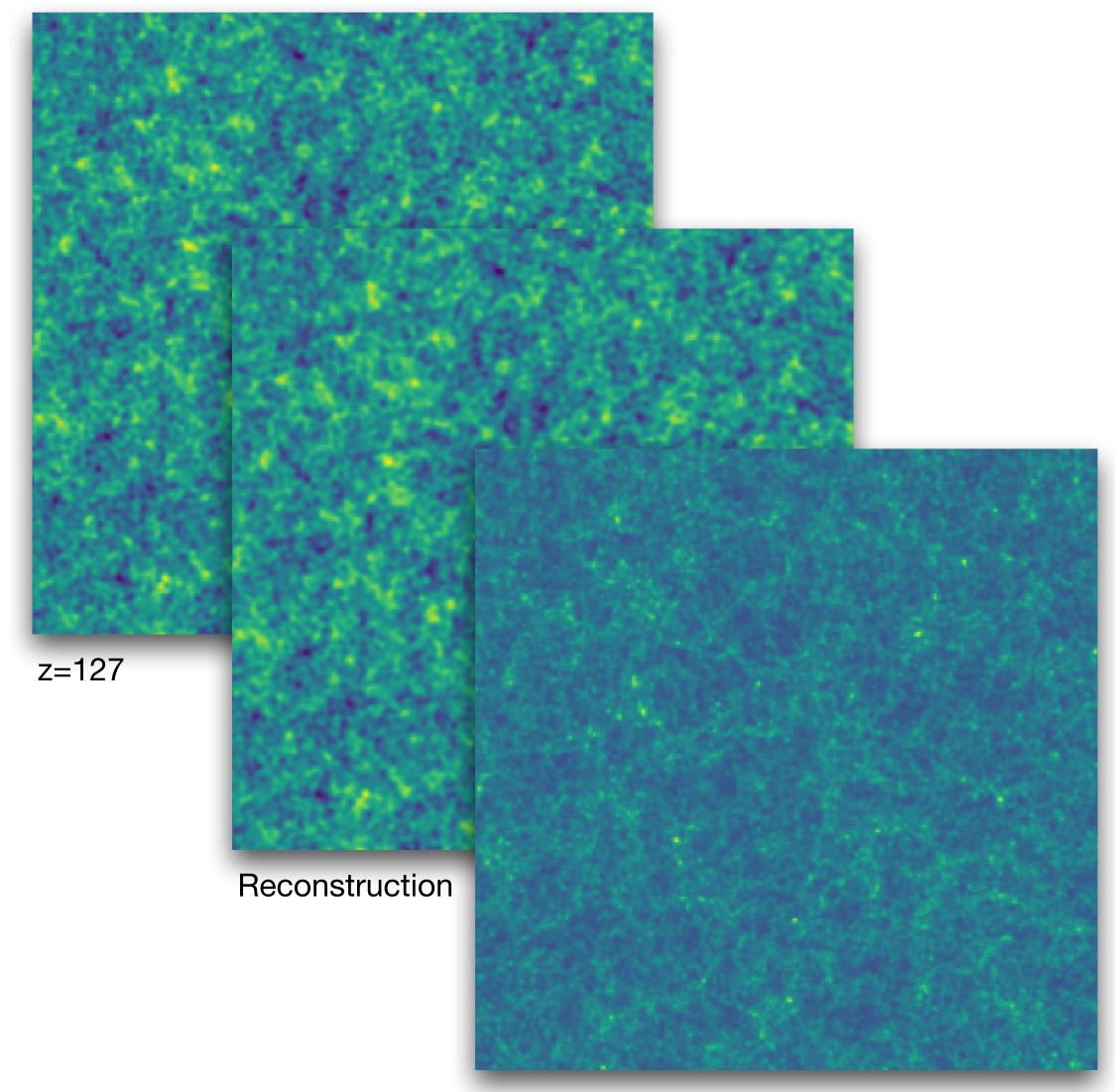
### Training 2305.07018 TF & Daan Meerburg

- 48 Quijote N-body z=0 & z=127 density field (256<sup>3</sup>) pairs @ fiducial cosmology
- $k_{\rm max} = 0.8 \, {\rm h/Mpc}$
- Loss: Pixel MSE
- ~ 4 hours of training (on 4xA100)

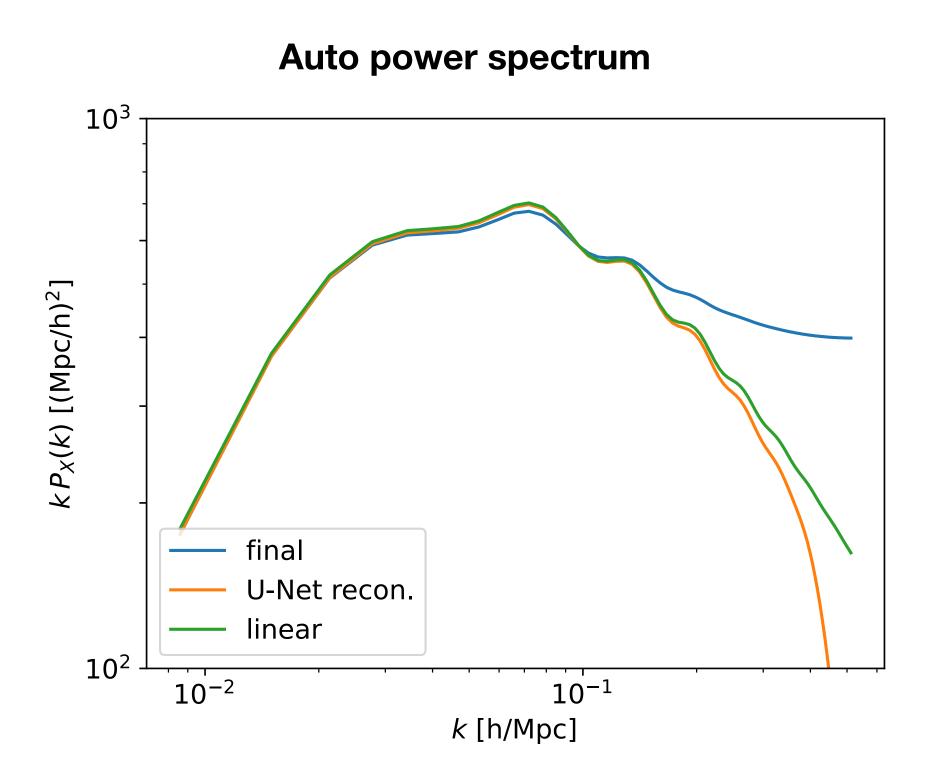


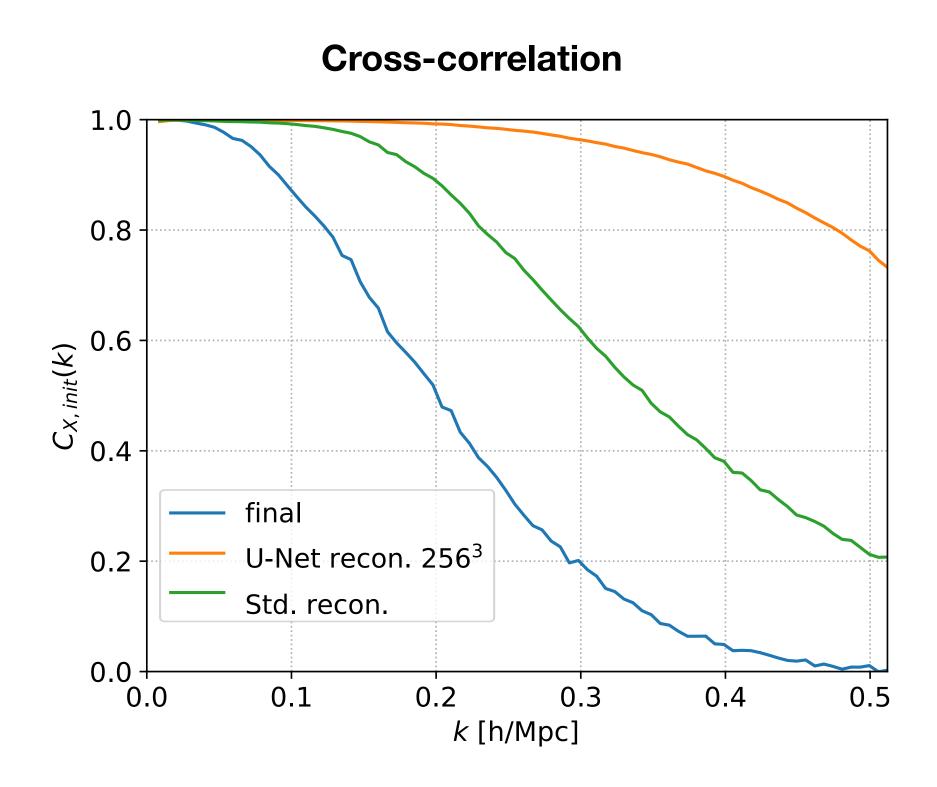
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# **Reconstruction quality** 2305.07018 TF & Daan Meerburg





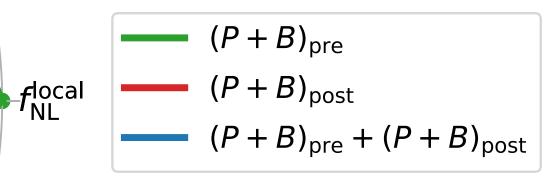
### Information content of P+B

$$F_{ab} = \frac{\partial \bar{D}}{\partial \theta_a} \cdot \left(C^{-1}\right) \cdot \frac{\partial \bar{D}}{\partial \theta_b}$$

- $D = \{P_{\text{pre}}(k), B_{\text{pre}}(k), P_{\text{post}}(k), B_{\text{post}}(k)\}$  up to k = 0.52 h/Mpc
- $\theta_a = \{f_{\mathrm{NL}}^{\mathrm{loc}}, f_{\mathrm{NI}}^{\mathrm{eq}}, f_{\mathrm{NL}}^{\mathrm{orth}}, h, n_s, \Omega_m, \Omega_b, \sigma_8\}$

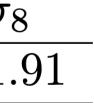
$$\sigma_a = \sqrt{(F^{-1})_{aa}}$$

### Improving constraints 2305.07018 TF & Daan Meerburg $f_{\rm NL}^{\rm equil}$ h 1.00 0.75 0.50 0.25 ns $\Omega_m$ $\sigma_8$ $\Omega_b$



$f_{ m NL}^{ m local}$	$f_{ m NL}^{ m equil}$	$f_{ m NL}^{ m orth}$	h	$n_s$	$\Omega_m$	$\Omega_b$	$\sigma_8$
3.65	3.54	2.90	2.43	1.98	1.64	2.56	1.

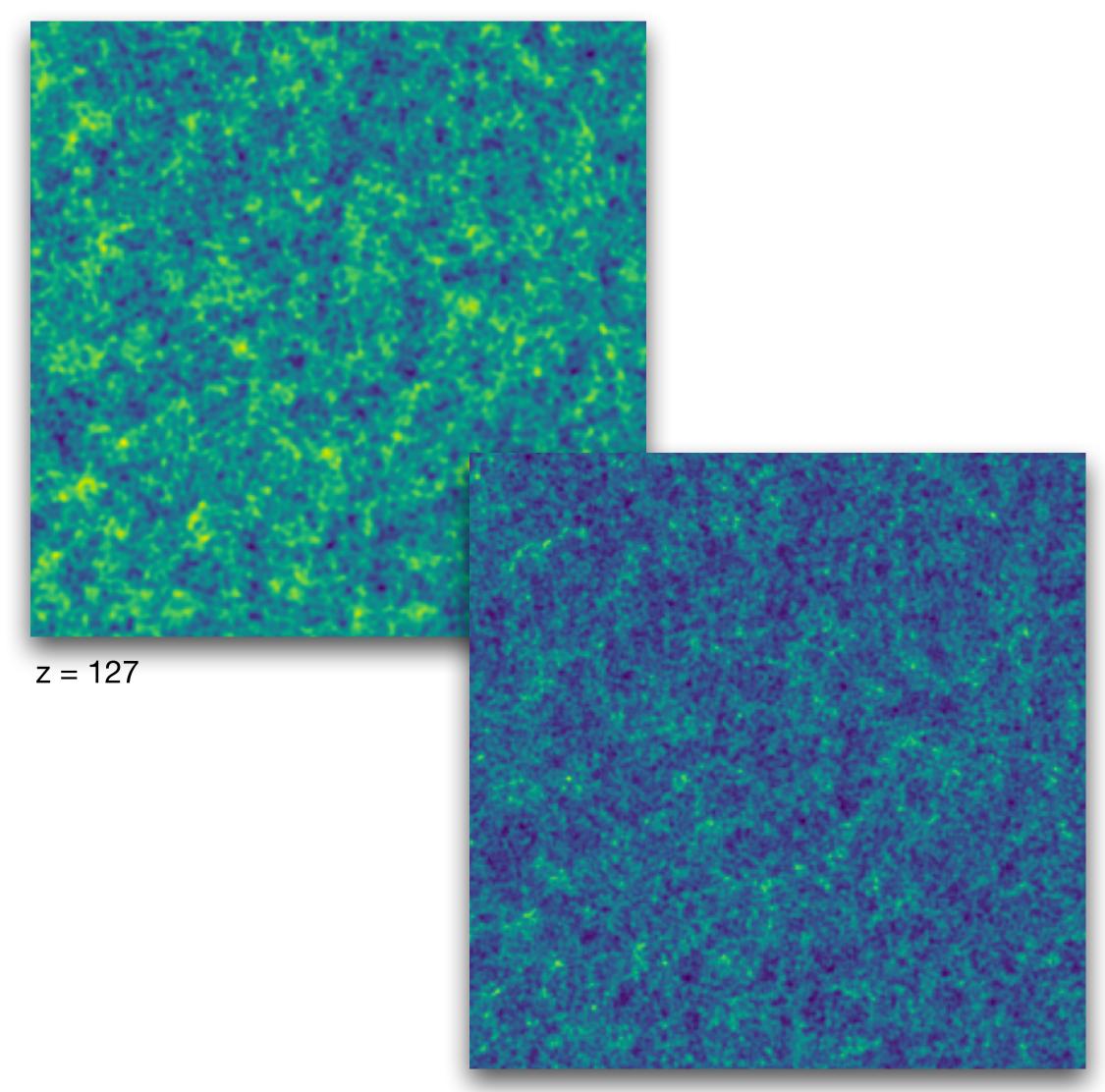
Relative improvement  $\sigma_a^{\text{pre}}/\sigma_a^{\text{pre+post}}$ 



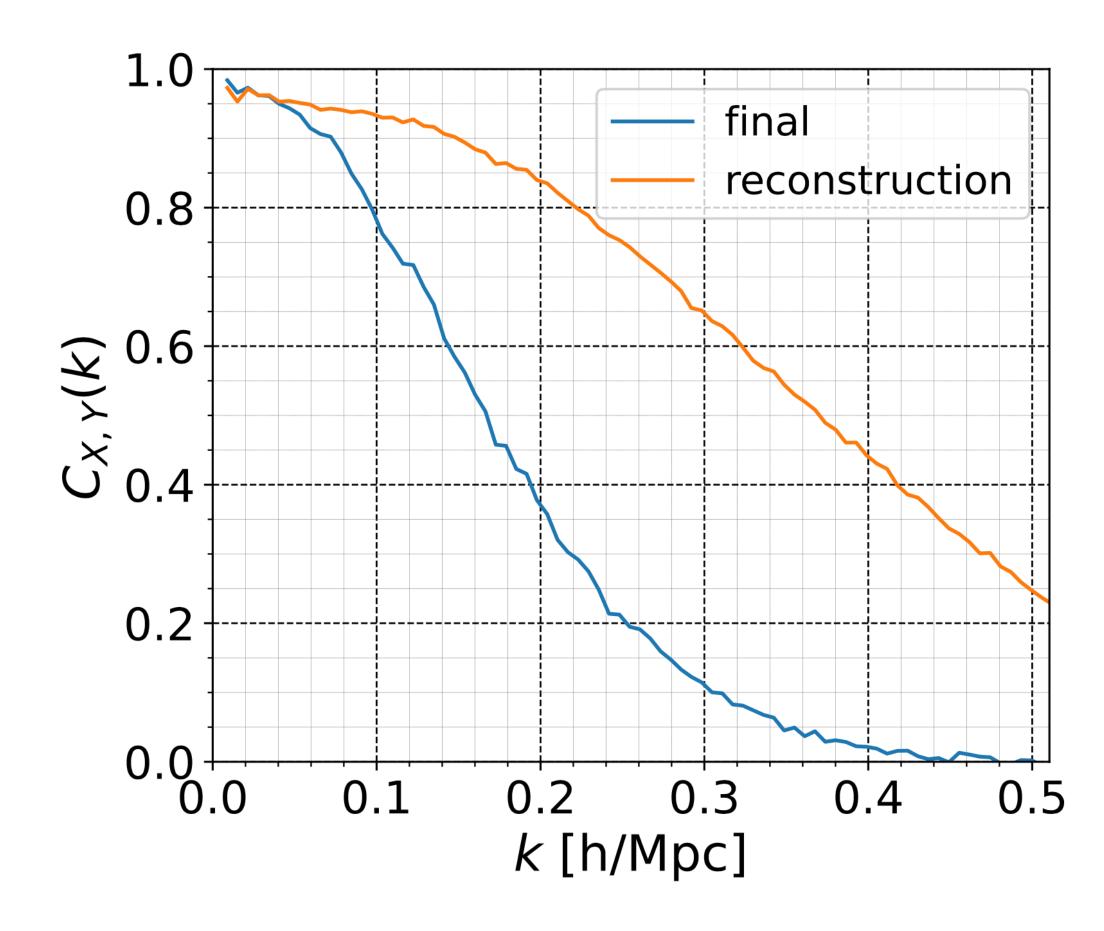
## Halo field

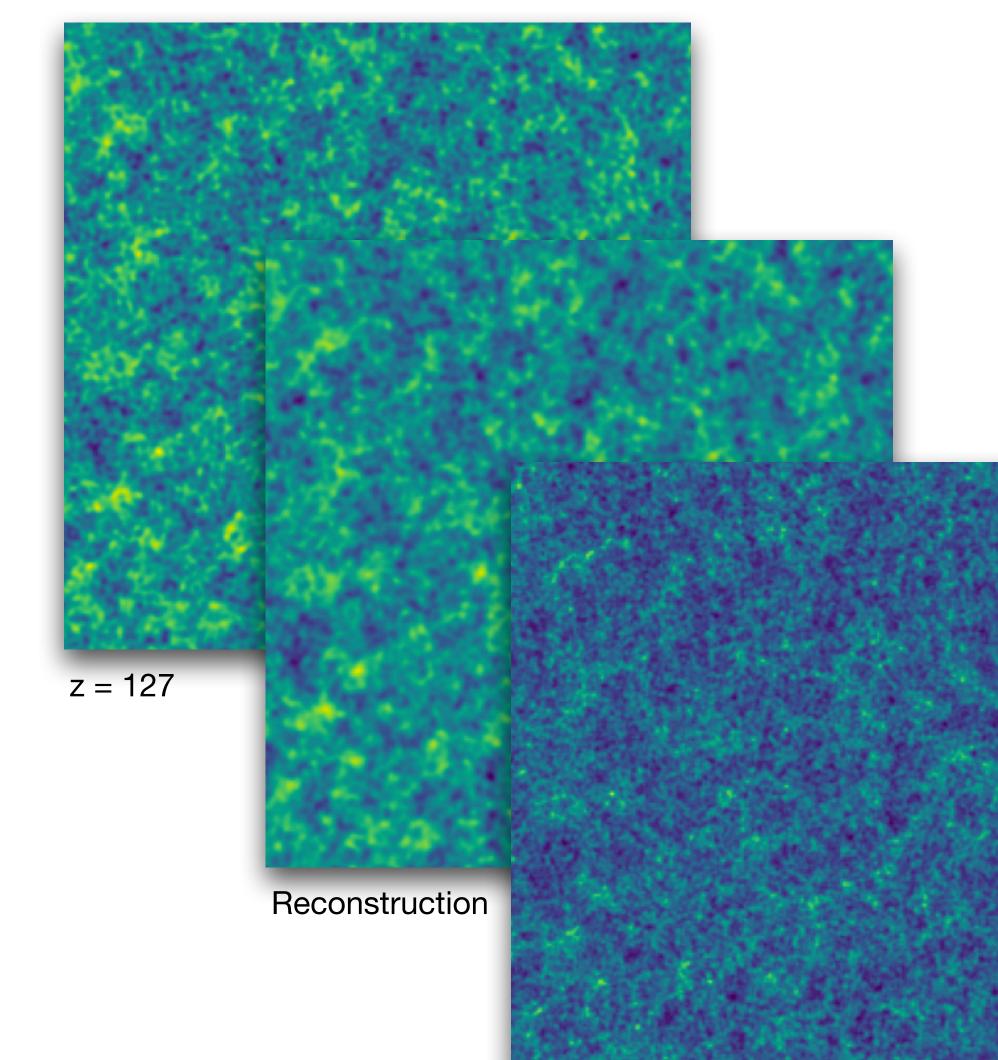
- Halo number density field + redshift-space distortions
- Shot-noise dominated
- Scale dependent bias for  $f_{\rm NL}^{\rm local}$

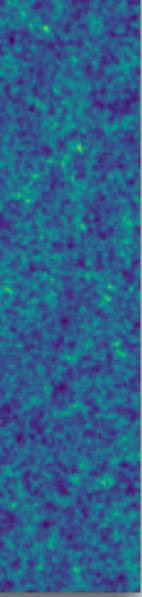
# Halo field: reconstruction



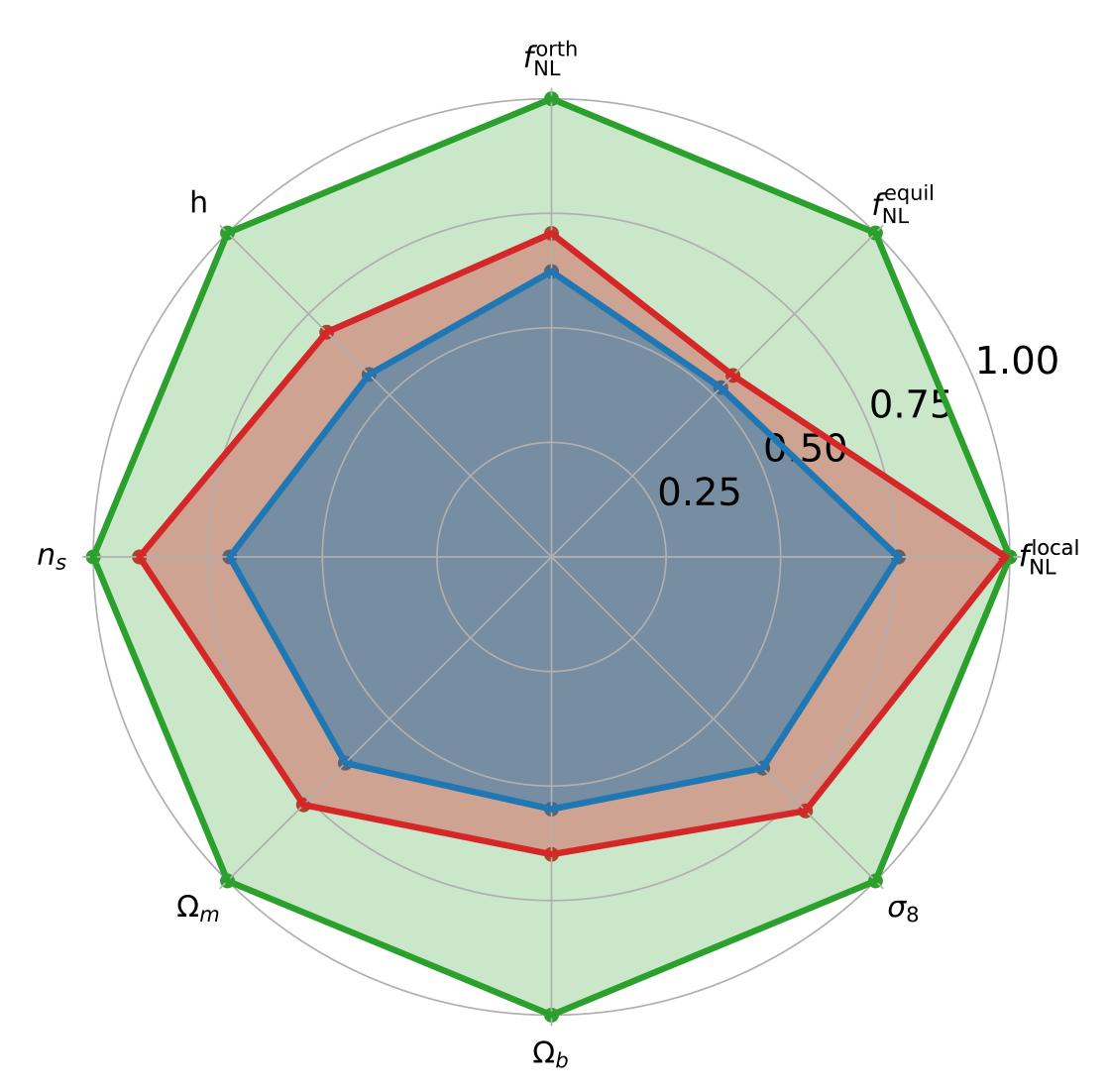
# Halo field: reconstruction

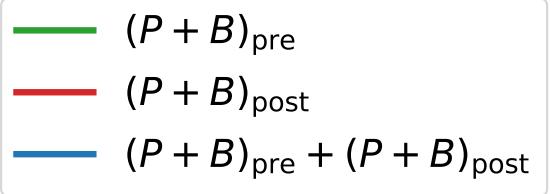




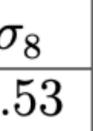


## Halo field





$f_{NL}^{local}$	$f_{NL}^{equil}$	$f_{NL}^{orth}$	h	$n_s$	$\Omega_m$	$\Omega_b$	σ
1.32	1.91	1.61	1.78	1.42	1.57	1.82	1.5



### **Conclusions & Outlook**

- Bispectrum is not optimal for pnG from LSS
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- Field level is the way to go
- Differentiable forward modelling
- Bayesian analysis



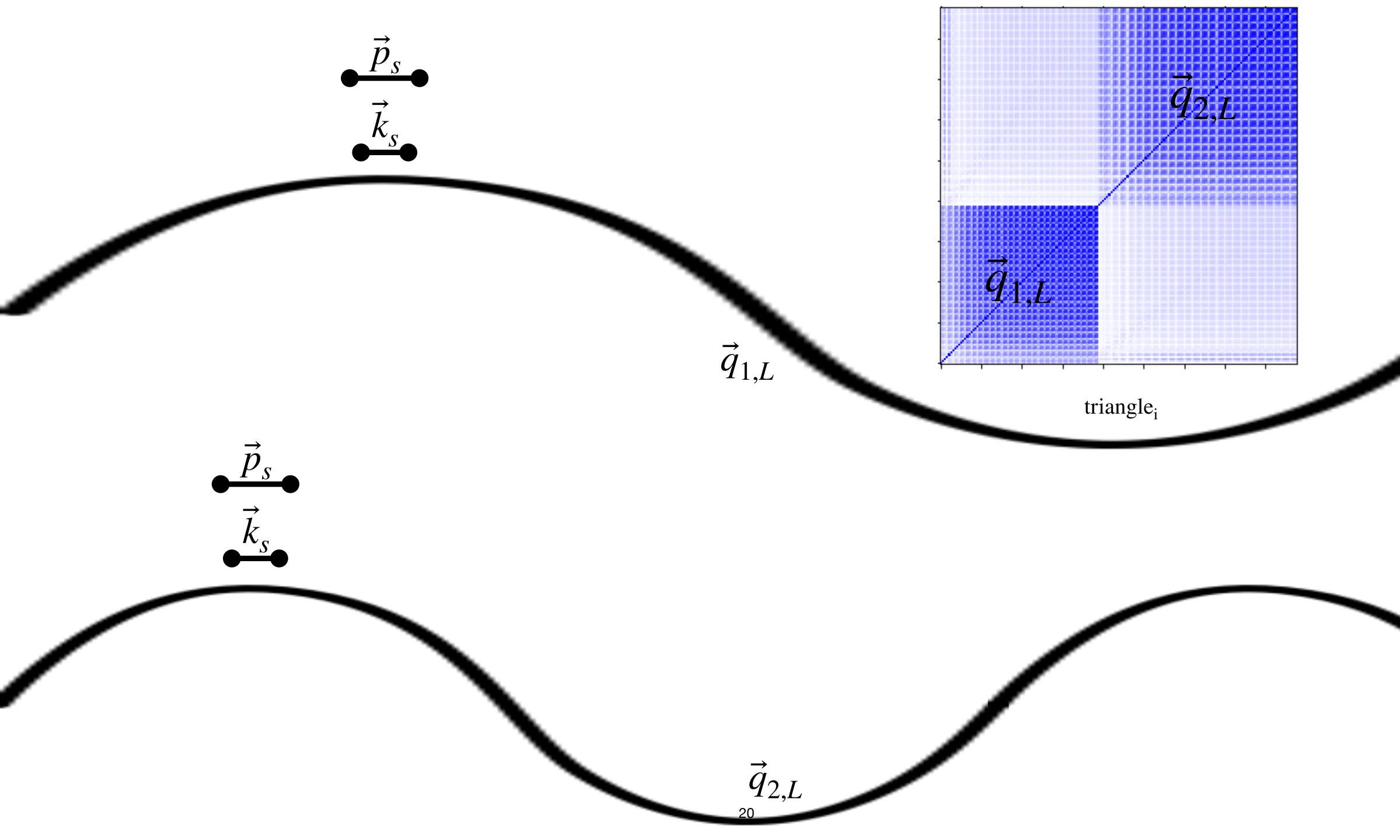


### Useful codes for the community

- Fast(est?) FFT bispectrum estimator on GPU (jax): **BFast** 
  - https://github.com/tsfloss/BFast
  - ~2300 triangles @ 256<sup>3</sup> grid in 0.5s
  - Differentiable soon

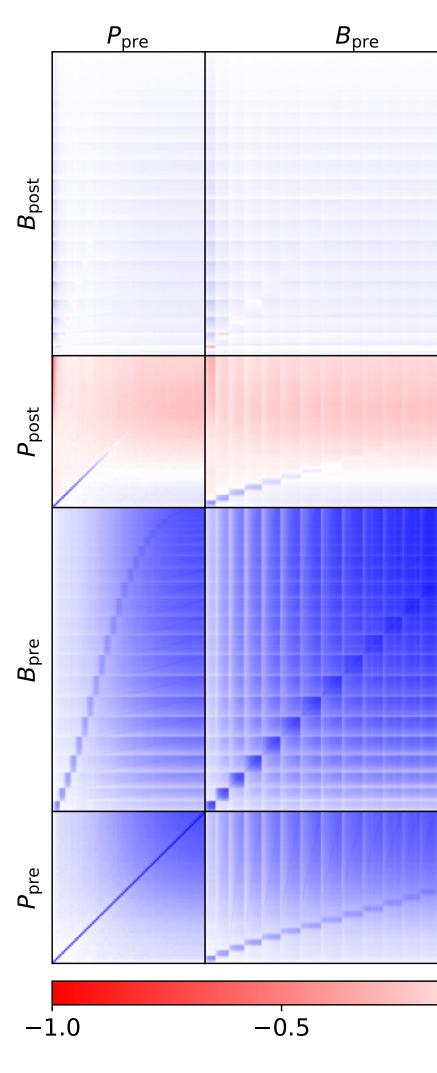
- **PolyBin3D** (Oliver Philcox & TF 2404.07249)
  - Unwindowed & local LOS power spectrum + bispectrum on CPU/GPU
  - https://github.com/oliverphilcox/PolyBin3D

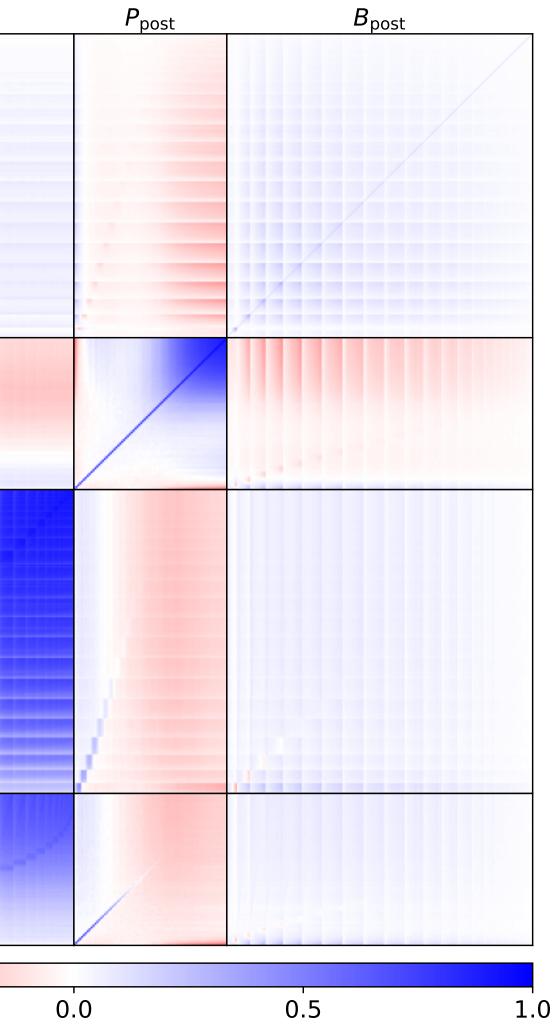
# **Backup Slides**



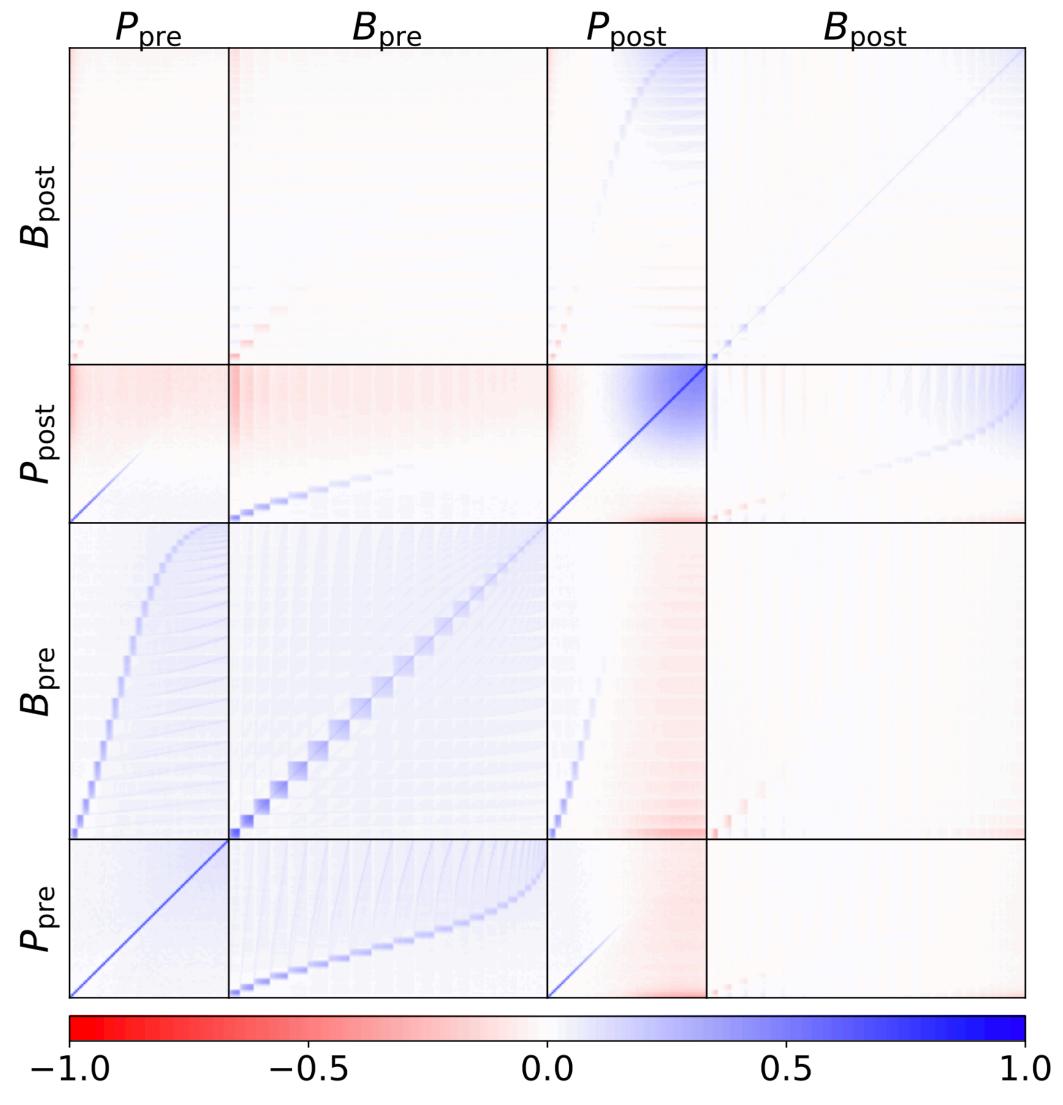


### **Reduced covariance (matter)**

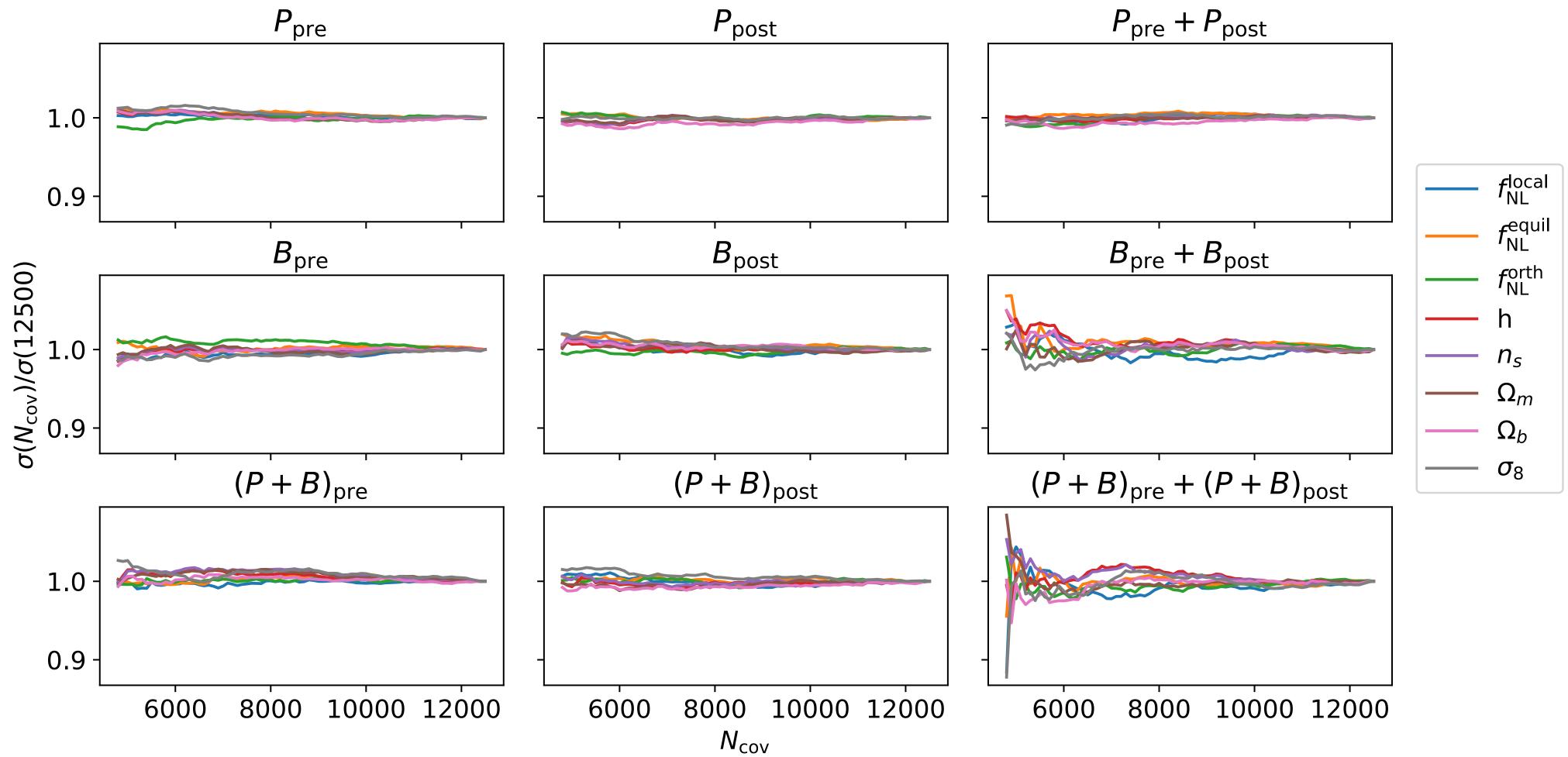




### **Reduced covariance (halo)**

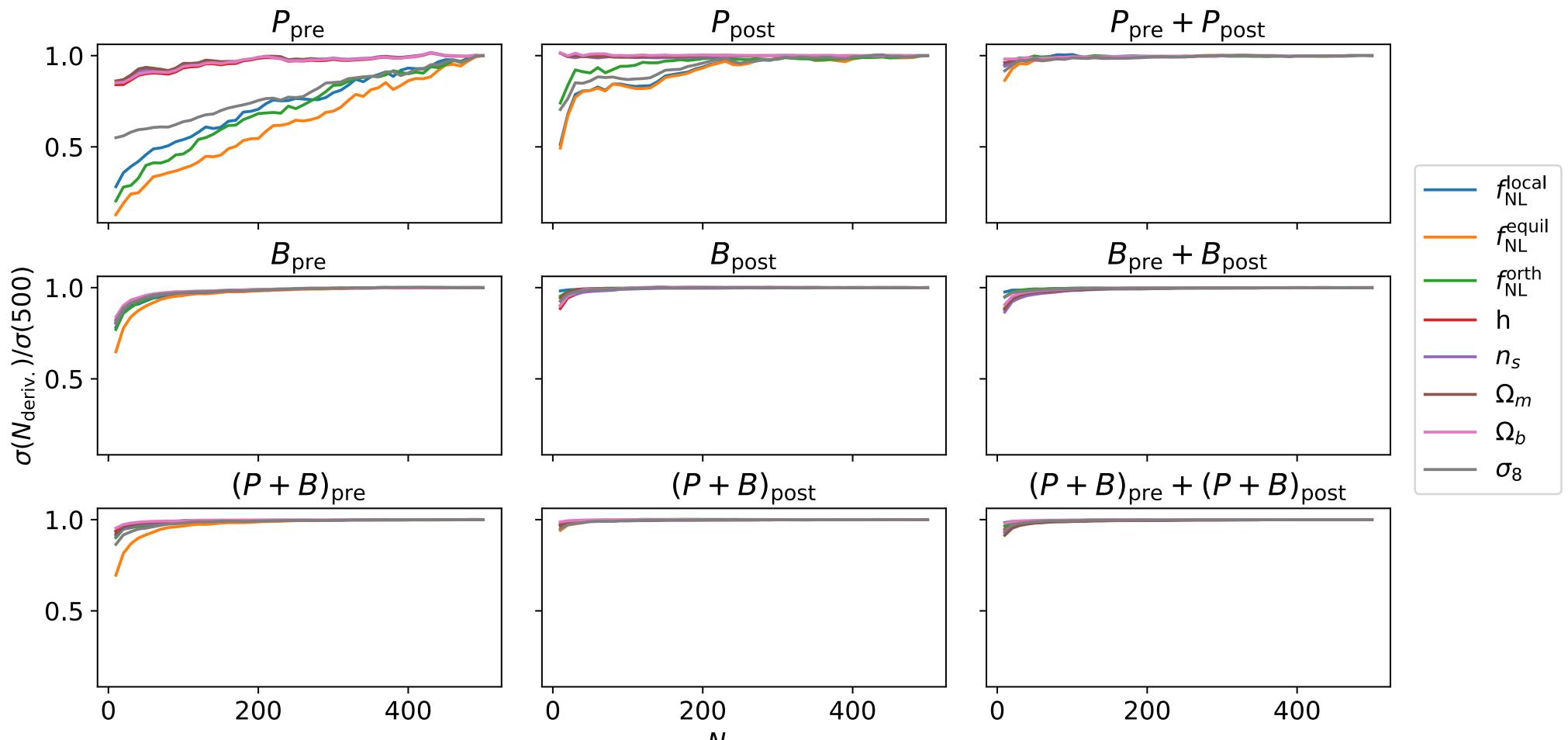


### **Convergence Tests: covariance**





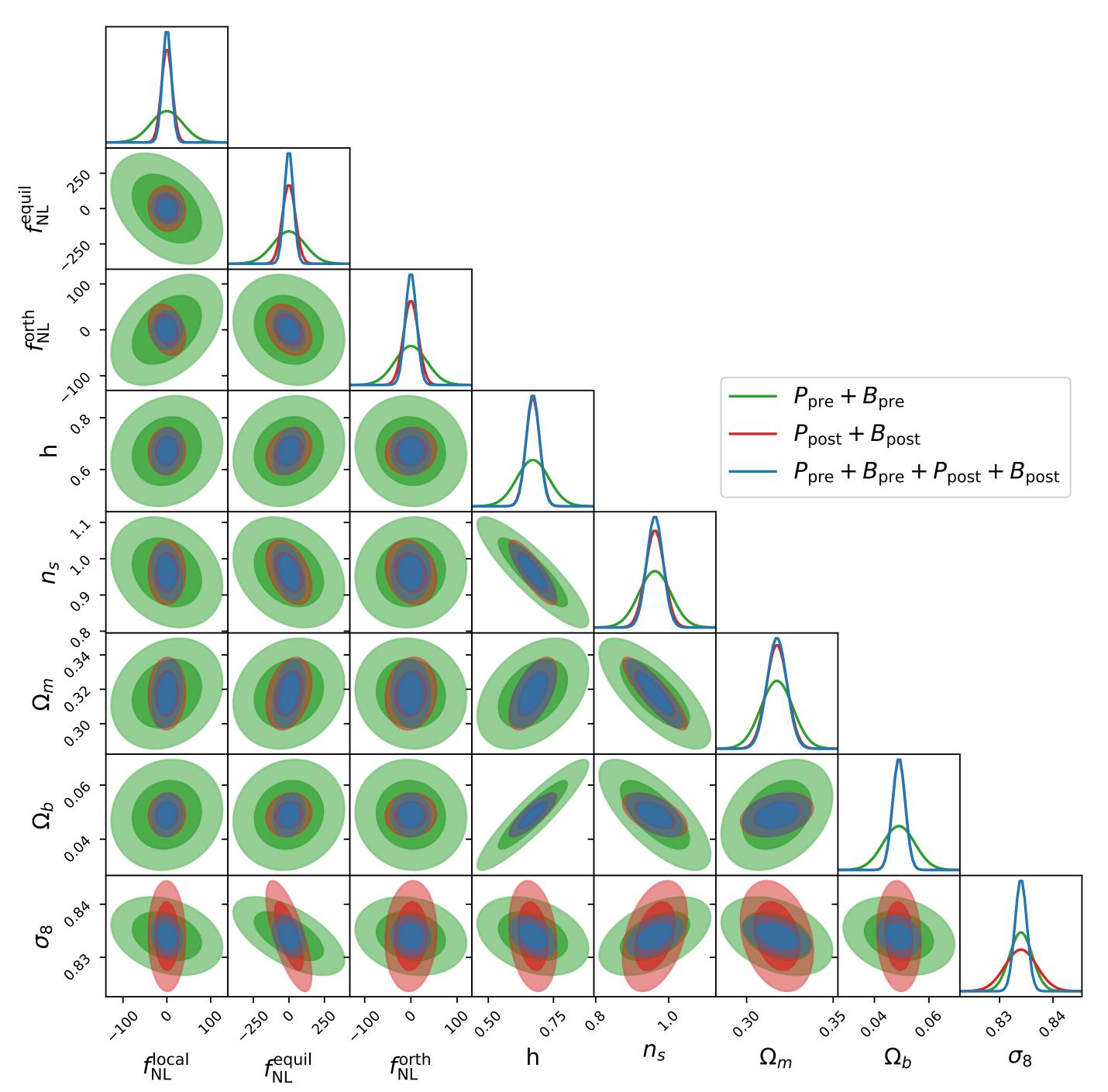
### **Convergence Tests: derivatives**



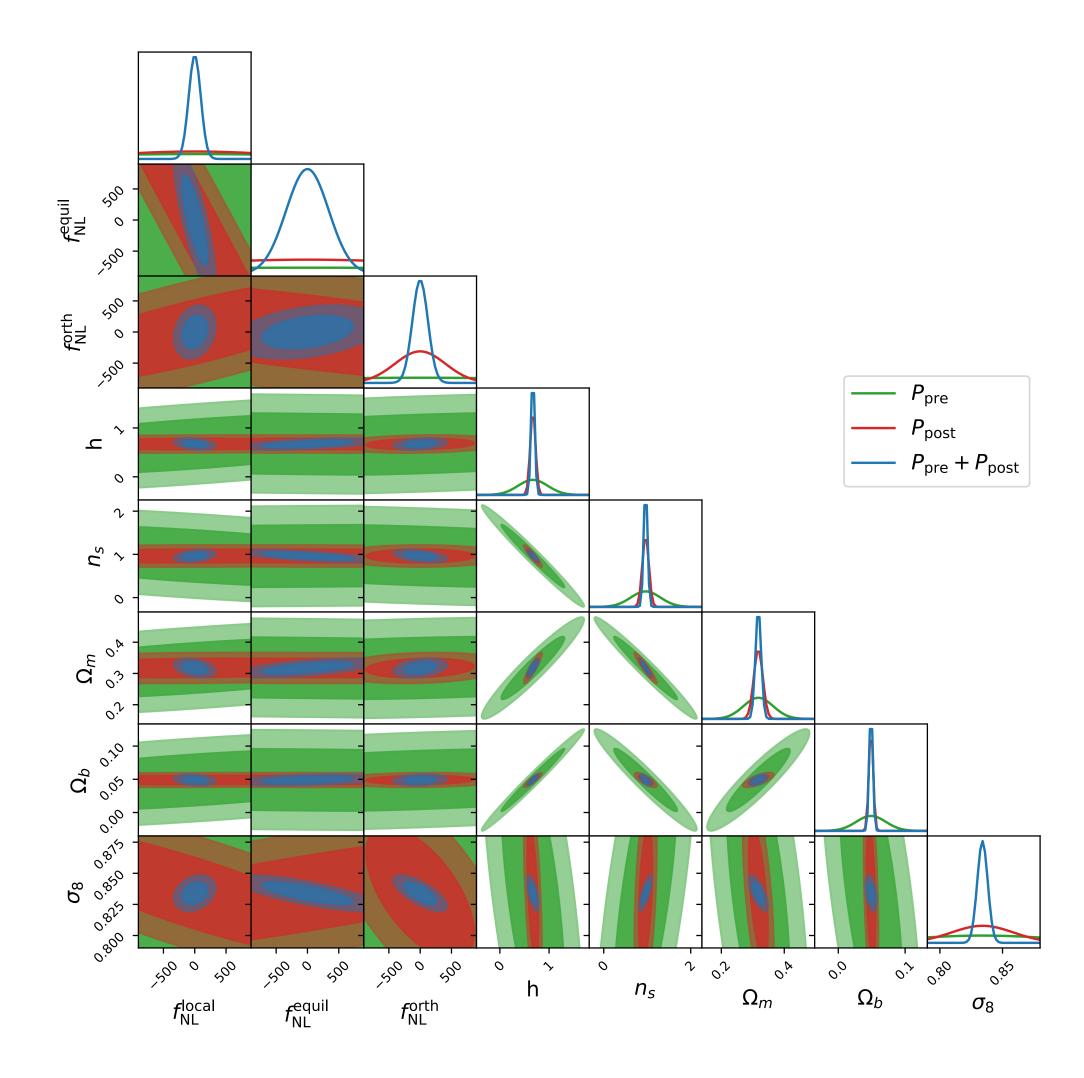
N<sub>deriv.</sub>

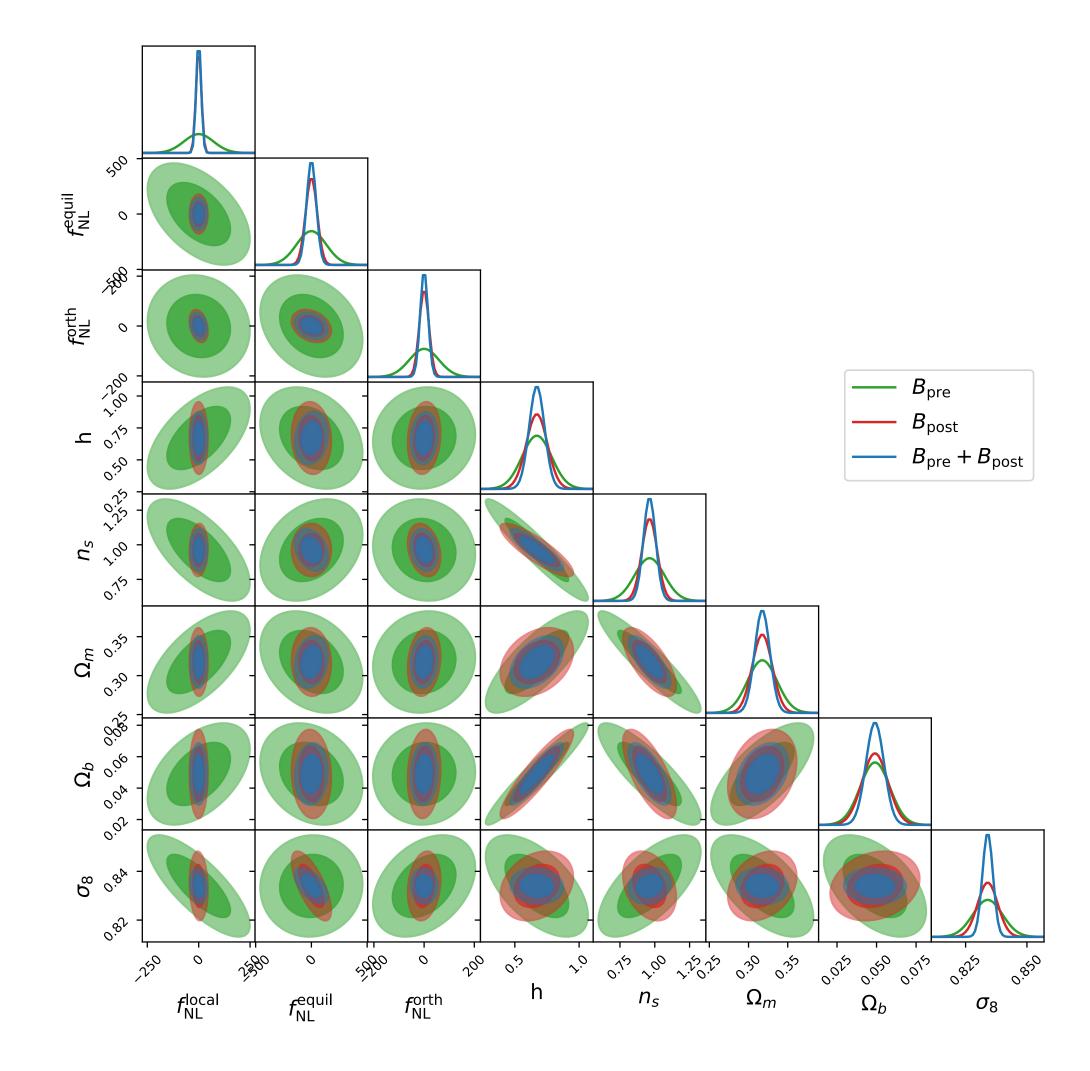
### **Contour Plots**

### **Power Spectrum and Bispectrum**



### **Contour Plots Power Spectrum or Bispectrum**





### Estimator

 $\hat{\theta}^a - \theta^a_{\text{fid}} = \sum_{b} (F^{-1})_{ab} \frac{\partial \bar{D}}{\partial \theta^b} \cdot C^{-1} \cdot (D_{\text{obs}} - \bar{D}_{\text{fid}})$